# Diagnosis and Monitoring of Alzheimer's Patients Using Classical and Deep Learning Techniques

M.Raza[a], M. Awais[b], W. Ellahi[c], N. Aslam[d], H. X. Nguyen[a], H. Le-Minh[d]

[a]Middlesex University, London, UK
[b]University of Leeds, UK
[c]National Database & Registration Authority, Pakistan
[d]Northumbria University, Newcastle, UK

## ABSTRACT

**Machine based analysis and prediction systems are widely used for diagnosis of Alzheimer's Disease (AD). However, lower accuracy of existing techniques and lack of post diagnosis monitoring systems limit the scope of such studies. In this paper, a novel machine learning based diagnosis and monitoring of AD-like diseases is proposed. The AD-like diseases diagnosis process is accomplished by analysing the magnetic resonance imaging (MRI) scans using deep learning and is followed by an activity monitoring framework to monitor the subjects' activities of daily living using body worn inertial sensors. The activity monitoring provides an assistive framework in daily life activities and evaluates vulnerability of the patients based on the activity level. The AD diagnosis results show up to 82% improvement in comparison to well-known existing techniques. Moreover, above 95% accuracy is achieved to classify the activities of daily living which is quite encouraging in terms of monitoring the activity profile of the subject.**

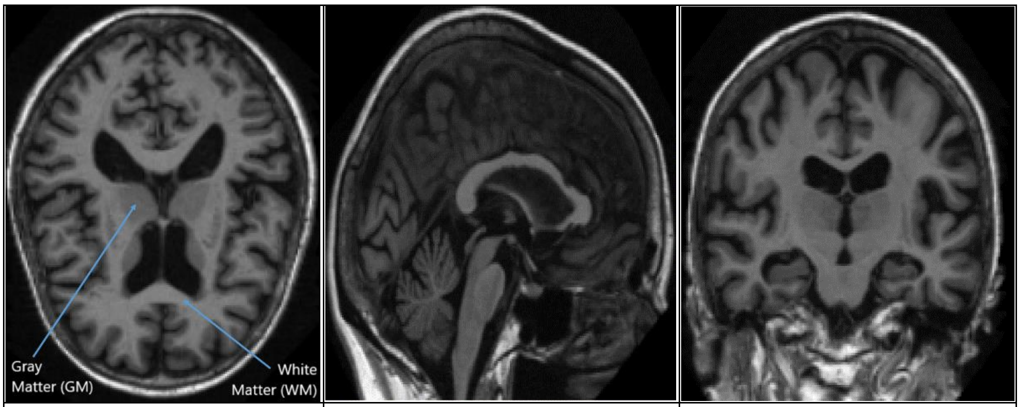
## 1. Introduction

Alzheimer's disease (AD) is one of the most common forms of dementia. About 60% to 80% of people with dementia develop AD. According to the report presented by the Alzheimer's disease international in 2016 ( Wymo, 2010), 47 million people are living with dementia. This number is expected to rise to 65.37 million and 115.4 million by year 2030 and year 2050 respectively. Dementia also has a huge economic impact. The total estimated worldwide cost of dementia as of present is US$818 billion ( Wymo, 2010). A huge majority of people with dementia have not received a diagnosis, and so are unable to access care and treatment. Even when dementia is diagnosed, the care provided is too often fragmented, uncoordinated, and unresponsive to the needs of people living with dementia.

Dementia is a neurological disorder and can be classified in several types. It is a degenerative brain disease which affects problem solving abilities, memory, language, physical activities and cause other cognitive disorders that affect the basic activities of daily life (ADLs). As the disease progresses, it damages that brain neurons which are responsible for carrying out basic daily life activities. The resulting problems of AD-like diseases are: confusion, disorientation, poor judgement, impaired communication and eventually difficulties in walking, swallowing and speaking (Association, 2017). In early stages of AD, memory loss is a common phenomenon. However, In the later stages of AD, patient cannot even perform necessary daily life activities and become totally dependent on others. In Table 1, the stages of AD are presented in detail. The table also represents the survival rate of alzheimer's patients over time and how physical activities affect this survival rate. The patients are divided in three categories: No Physical activity (NPA), Moderate Physical Activity (MPA), High Physical Activity (HPA) (Scarmeas et al., 2011). The findings suggest that by incorporating physical activity

Mohsin Raza and Huan X. Nguyen are with Faculty of Science and Technology, Middlesex University, London UK. Email: {m.raza, h.nguyen}@mdx.ac.uk
Mohammad Awais is with School of Psychology, University of Leeds, UK. Email: m.awais@leeds.ac.uk
Waqas Ellahi is with National Database & Registration Authority, Pakistan. Email: waqas_ellahi@yahoo.com
Nauman Aslam and Hoa Le-Minh are with Department of Computer Science and Digital Technologies and Mathematics, Physics and Electrical Engineering Departments respectively, Northumbria University UK. Email: {nauman.aslam, hoa.le-minh}@northumbria.ac.uk

can significantly prolong the survival of alzheimer's patients (Beckett, Ardern, & Rotondi, 2015; Debove, Bru, Couderc, Noé, & Paillard, 2017; Scarmeas et al., 2011).




| (a) | (b) | (c) |
|---|---|---|

**Fig. 1: MR Image Planes (a) Axial (b) Sagittal (c) Coronal**

There are no specific remedies or cure of AD-like diseases (Prince, Albanese, Guerchet, & Prina, 2014), however, early diagnosis can help in improving patient's quality of living. The most suitable method for diagnosis of AD-like diseases uses Magnetic Resonance Imaging (MRI) (Chaves, Ramírez, Gorriz, & Initiative, 2013; Martínez-Murcia et al., 2012; Ramaniharan, Manoharan, & Swaminathan, 2016). In MRI, strong radio waves and magnetic field are used for generation of images of body organs. The different types of tissues such as white matter (WM) and grey matter (GM) are highlighted with different contrasts. As such, MRI can be employed to diagnose and study the diseases, which affect the GM and WM differently. Three different planes Axial, Sagittal and Coronal are generated from MRI as shown in Fig. 1 (taken from the Open Access Series of Imaging Studies (OASIS)) (Marcus, Fotenos, Csernansky, Morris, & Buckner, 2010). These planes are perpendicular to each other and are analysed using classical and deep machine learning techniques to diagnose AD-like diseases.

Once a patient reaches stage-2 of AD, the brain tissue shrinking, nerve cells death and tissue loss in brain affects different cognitive abilities, resulting in functional impairment. These changes in the brain are hard to track and therefore, cannot be used as a metric for evaluating stages of functional impairment in the patients and level of support they need to resume their daily life. Since functional impairment is one of the core symptoms of AD progression, it can be used to accurately evaluate needs for assistance. The most accurate measure of functional impairments is the decline in ADLs over the course of time (Leger et al., 2017). Monitoring ADLs of alzheimer's patients not only provide the measure of brain tissue degradation, it also helps to delay disease progression, thus slowing down the tissue degeneration process. A report by World Health Organization (WHO, 2015) on enhancing physical activity suggests that promoting physical activity in daily life improves mental health by overcoming depression, stress reaction and anxiety. Consequently, it can possibly reduce or delay the effects of AD and other types of dementia. Physical activities also improve cerebral perfusion (blood flow to the brain regions), reduce neuronal loss (loss of neurons) and preserve brain volume in the regions susceptible to AD-like diseases (Stephen, Hongisto, Solomon, & Lönnroos, 2017).

In this paper, novel research is carried out to not only improve the diagnosis accuracy of AD-like diseases but to also interlink ADLs with the AD-like diseases to prolong brain functionality, reduce brain tissue degradation and accurately measure the functional impairment in alzheimer's patients over the course of time. In particular, the proposed work offers framework to identify/diagnose ADLs and AD-like diseases using both classical and deep learning techniques. The MRI based diagnosis of AD is achieved through transfer learning where modified AlexNet (Krizhevsky, Sutskever, & Hinton, 2012) is proposed. To further improve the accuracy of the proposed system most informative MRI slices are identified and used for training and diagnosis. To classify ADLs, a Support Vector Machine (SVM) based classifier is used to accurately identify the ADLs. A detailed discussion on the datasets used, system model and performance analysis is presented in Section III and IV. Main contributions of the proposed work are as follows

- To the best of our knowledge, this is the first work to consider both diagnosis of alzheimer's and extended monitoring without the involvement of direct human intervention.
- The proposed diagnosis of AD-like diseases is talented by deep learning framework which has higher accuracy in comparison to state of the art.
- Machine based analysis of ADLs is proposed which monitors the daily life activities of alzheimer's patient with high accuracy and provide additional assistance
- An automated machine-based monitoring system is introduced to facilitate human intervention. Recommendations and Guidelines are also provided for framework development to ensure alzheimer's patients' independence (where possible) and technology-based assistance.

**Table 1 Overview of Alzheimer's Disease and Impact of Physical Activity**

| Stages | | Condition | Symptoms | Disease detection using memory tests | Average duration | Time in Years | Survival Rate (Norm.) | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | NPA | MPA | HPA |
| EARLY | Stage-1 | No Impairment | 1. No detectable Symptoms<br>2. No memory loss | Unlikely to be detected | Several Years | 1 | 1 | 1 | 1 |
| | Stage-2 | Very Mild Decline | 1. Slight memory problems<br>2. losing things | Unlikely to be detected | - | 2 | 0.95 | 0.98 | 0.98 |
| | Stage-3 | Mild Decline | 1. Difficulty in planning and organizing<br>2. Forgetting names of new acquaintances<br>3. Difficulty in finding right word during conversations | Physicians might detect impaired cognitive functions | Up to 7 Years | 3 | 0.90 | 0.94 | 0.96 |
| | | | | | | 4 | 0.85 | 0.92 | 0.94 |
| MIDDLE | Stage-4 | Moderate Decline | 1. Difficulty with simple arithmetic<br>2. Forgetting details of their life history<br>3. Inability to manage finance and pay bills | Physicians will detect moderate impaired cognitive functions | 2 Years | 5 | 0.78 | 0.89 | 0.91 |
| | | | | | | 6 | 0.68 | 0.82 | 0.88 |
| | Stage-5 | Moderately Severe Decline | 1. Significant confusion<br>2. Inability to recall simple details about themselves<br>3. Difficulty dressing appropriately | Symptoms are obvious and easily spotted | 1.5 Years | 7 | 0.50 | 0.72 | 0.79 |
| | | | | | | 8 | 0.33 | 0.60 | 0.68 |
| LATE | Stage-6 | Severe Decline | 1. Unawareness of environment and surroundings<br>2. Loss of Bladder control<br>3. Inability to remember personal details<br>4. Inability to recognize faces except close ones | - | 2.5 Years | 9 | 0.23 | 0.46 | 0.55 |
| | Stage-7 | Very Severe Decline | 1. May loose ability to swallow<br>2. Can't perform any activities of daily life | - | Patients rarely reach this stage | 10 | 0.09 | 0.28 | 0.37 |

## 2. Related Work

In the last decade, many researches (ER, Varma, & Paul, 2017; J. Zhang, Gao, Munsell, & Shen, 2016) have been conducted to diagnose AD using classical machine learning techniques such as Principal Component Analysis (PCA), SVM. Some of the renowned works are listed as follows. In (ER Varma, & Paul., 2017), the Gray-Level Co-occurrence Matrix (GLCM) was used as a feature and SVM based classification was implemented. In this work, Contrast Limited Adaptive Histogram Equalization (CLAHE) was performed to pre-process the raw imagery before extracting the features. An optimized method for AD diagnosis was proposed (Zhang et al., 2016) and three steps were performed: landmark definition, landmark detection and classification between AD and healthy control (HC). In landmark definition (local morphological features such as histograms, oriented energies and local minima in the p-values map) statistical differences between AD and healthy control (HC) were used to differentiate between the two. Suitable training dataset was also identified in landmark definition step. In landmark detection, A pre-trained landmark detection model was proposed to effectively identify AD landmarks in each test dataset. Finally, an SVM classifier, trained on a landmark-based morphological features, was used to differentiate between HC and AD images. In (Zhang & Wang, 2015), a Displacement Field (DF) was estimated between a normal brain and an alzheimer's patient's brain. For evaluation purposes, DF was used as features, reduced by PCA, and finally classified by three different variants of SVM. In (Zhang et al., 2015), the feature eigen brain was generated from PCA, which was fed into the SVM to classify HC and AD.

Recently, the deep learning methods have shown significant performance improvements over classical method in AD diagnosis. Unlike the classical machine learning algorithms where handcrafted features are extracted from the dataset, deep learning techniques extract optimized features from the dataset. The feature set is then fed to neural network for improved accuracy. It is also noted that recently developed deep learning methods have performed much better than classical methods in many research problems. Some of these are listed as follows.

In (Gupta, Ayhan, & Maida, 2013), the initial weights were determined by training the sparse auto-encoder. These weights were used for convolution neural network (CNN) to classify AD and HC. This method was further improved in (Payan & Montana, 2015) by applying 3D convolution instead of 2D convolution. In (Liu et al., 2014), stack autoencoder was used to generate features from the MRI and softmax regression layer was proposed for classification.

Along with the diagnosis of AD, identification of means to slow down brain tissue degradation and monitoring patient's activities also play an important role in defining accurate level of assistance, needed by the patient. There are several studies (Garuffi et al., 2013; Morris et al., 2017; Panza et al., 2018) which monitored the effect of exercises on AD population and how AD affects ADLs. For instance, in (Garuffi et al., 2013), authors investigated the effect of activities on AD population and found that resistive training improves the balance, lower limb strength and flexibility in AD population. However, most of these studies utilize the assessment tools which are questionnaire based and/or self-reported by the patient/observer, which biases (over/under estimates) the actual amount of physical activity performed (Cleland et al., 2014).

As an alternate, microelectromechanical systems (MEMS) technology based inertial measurement units (IMUs) can be helpful in designing personal health care systems and assistive technologies to measure the level of activities performed. The recent advancements in such devices (miniaturization, light weight, low cost, long-battery life and fast-processing capabilities) have also made the transition much more easier and effective (Troiano, McClain, Brychta, & Chen, 2014). Recently, many systems have been developed to objectively classify the ADLs (Awais et al., 2016; Ayachi et al., 2016; Ordóñez & Roggen, 2016). However, majority of the existing studies focus on the healthy population whereas a very few systems can be found which utilize alzheimer's disease based population (Gago et al., 2014; Hsu et al., 2014; Wang, Chung, Hsu, Pai, & Lin, 2013). The limited few inertial sensors based developed systems, used for AD patients show the potential of objectively quantifying the movement patterns. However, all these systems only explored the walking activity and none of them explored the other commonly performed ADLs: sitting, standings, walking, lying, ascending stairs and descending stairs. These ADLs are quite relevant for the AD population as they can provide not only the everyday patterns of the active and sedentary activity periods but also can offer insight on certain interventions/medications by caregivers and clinical staff. It is worth mentioning that the existing state of the art methods for detecting AD only focuses on diagnosis stage and post diagnosis stage in often ignored. However, it is quite relevant to monitor the ADLs of the patients diagnosed with the early stages of AD as with effective feedback on ADLs can slow down the degenerative process of the brain tissues and help improve the patients' routine life with improved functional independence. This is evident in (Arcoverde et al., 2008; Larson et al., 2006) that by incorporating healthier lifestyle and improved physical activities can leave positive impact on AD patients.

## 3. Proposed System Model

In this section, the proposed system model for diagnosis of AD-like diseases and classification of ADLs is presented. At first, system for the diagnosis of AD-like diseases is proposed. To offer extended monitoring of the patient's condition (with the passage of time) and to evaluate impact of alzheimer's on one's daily life, a framework for classifying ADLs is proposed. The proposed ADLs classifier categorizes daily life activities and can be used to analyze brain tissue degradation for alzheimer's patients based on ADLs. The use of wearable sensors to evaluate ADLs provides insight into the level of support needed by the patient. It also offers means to track the activity cycle of the patients to prolong the healthy living and to resist the mental degradation.

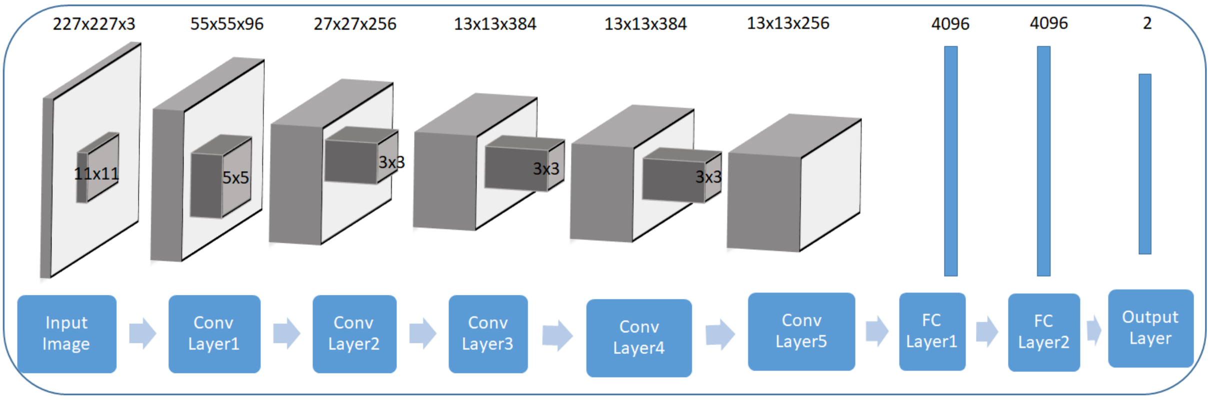


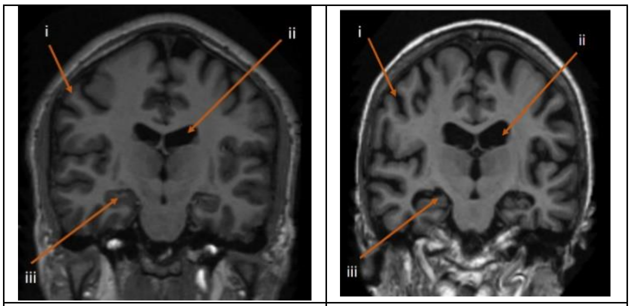

**Fig. 2: Modified AlexNet Architecture**

### 3.1 AD classification

As discussed earlier, deep learning methods perform better than classical techniques. However, the performance of deep learning methods depends on the availability of large datasets. In medical problems, the presence of large dataset is a big challenge. Data annotation by the trained physicians is expansive and due to ethical and security reasons cross institution use is also limited. This gives rise to of overfitting and underfitting of the classifier. The problem can be handled by using the transfer learning techniques and data augmentation method.

The deep learning models developed for AD classification only use one layer of CNN (Gupta, Ayhan, & Maida, 2013; Payan & Montana, 2015; Liu et al. 2014) which limit their capabilities of extracting complex patterns from MRI images. Therefore, the current work proposes a modified architecture of AlexNet (Krizhevsky et al., 2012) (winner of ImageNet large-scale visual recognition challenges (ILSVRC) 2012, by achieving 15.3% top-5 error rate) is used as a pertained model which was originally trained for object recognition and only parameters of fully connected layer (FC) are retrained for AD-like diseases classification. It has eight layers for learning. Five of these layers are used for convolution with sub pooling layers and three as fully connected layers. Output of fully connected layers is fed into the softmax for a distribution against binary classes (AD vs HC). The first convolutional layer uses 96 kernels of size $11\times11\times3$ with 4-pixel stride and filters the $227\times227\times3$ input images. The output of this layer is fed into the second convolutional layer, which filters this output using 256 kernels of size $5\times5\times48$. The third convolutional layer, connected to output of second convolutional layer, uses 384 kernels of size $3\times3\times256$. The fourth and fifth convolutional layer use 384 and 256 kernels respectively. There are 4096 neurons in each of fully connected layers. For model training, the stochastic gradient descent is used, while equal learning rate is used for all layers. In the proposed method, the output from the AlexNet classifier is modified to two categories (AD vs HC) for binary classification. The data augmentation method proposed in paper uses twenty central slices of the coronal plane instead of only one slice due to the high information content present in the central slices. It was observed that using highly informative images for training purposes improved system robustness.

We used the AlexNet model that takes a 2-d image as an input whereas our brain MRI data is 3-d. Data permutation is used in which multiple slices (Central 20 slices) are extracted from MRI brain data to increase training samples. As discussed earlier, the central slices have more tissue portion than the boarder slices. Since the tissues are biomarker of AD, central slices help the system to classify AD-like diseases accurately. The slices at the border have more portion of the bones and skulls and prove less informative rather misleading for AD-like diseases classification system. Therefore, the central 20 slices are used for the training purposes.




(A) (B)

**Fig. 3: Difference between (A) Healthy brain and (B) an AD brain. (i) Cerebral cortex (ii) Ventricle, and (iii) Hippocampus**

**Table 2. Demographics of Dataset**

| Name | Class | # of Subject | Sex | | Age (Mean) | # of MRI scans |
|---|---|---|---|---|---|---|
| | | | M | F | | |
| OASIS | AD | 100 | 41 | 59 | 76.76 | 100 |
| | HC | 316 | 119 | 197 | 45.09 | 316 |
| ADNI | AD | 200 | 103 | 97 | 76.05 | 530 |
| | HC | 232 | 113 | 119 | 76.18 | 877 |

| Slice # | Subject 1 | Subject 2 | Subject 3 |
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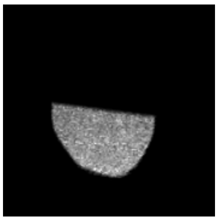
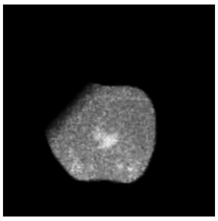
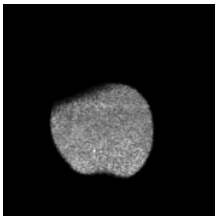
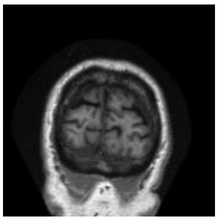
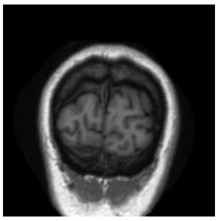
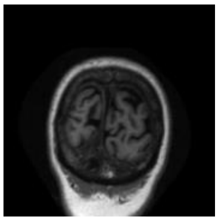
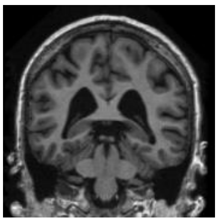
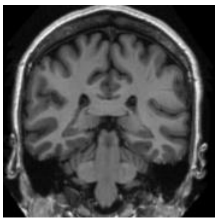
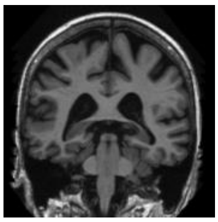
| **1** |  |  |  |
| **30** |  |  |  |
| **87** |  |  |  |

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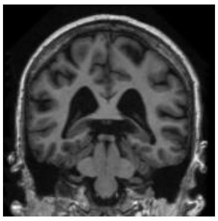
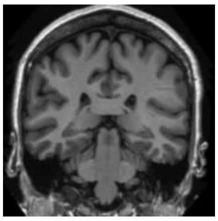
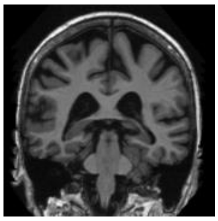
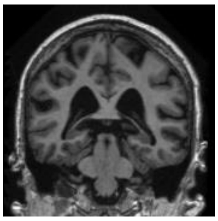
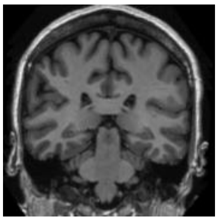
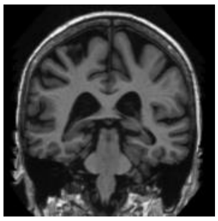
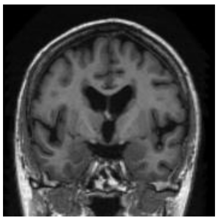
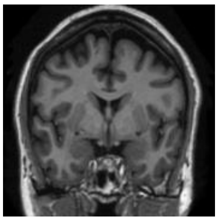
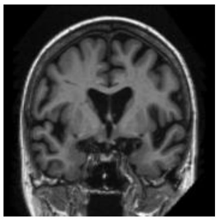
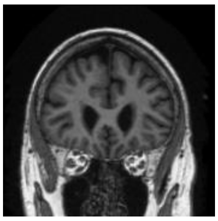
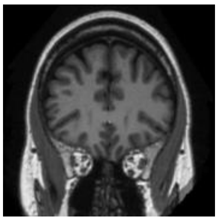
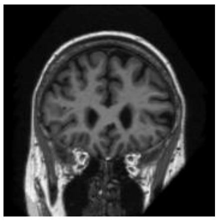
| **88** |  |  |  |
| **89** |  |  |  |
| **120** |  |  |  |
| **150** |  |  |  |

**Fig. 4: MRI Scans of Different Subjects at Different Slices**

Performance of the proposed method is tested using two widely used datasets, OASIS and alzheimer's disease neuroimaging initiative (ADNI) (Jack et al., 2008). Since several existing works used either OASIS or ADNI, selection of these datasets allows fair comparison of the proposed work with the existing techniques. The OASIS (Marcus et al., 2010) MRI dataset is divided in two categories: longitudinal and cross-sectional. The longitudinal dataset provides information on growth of AD over time whereas the cross-sectional dataset offers single MRI scans of subjects. The cross-sectional dataset is used for classification where a total of 416 subjects of ages 18 to 96 are provided in this dataset. ADNI has a total of 843 MRI scans with 1.5T scanner intensity field. In ADNI dataset, multiple scans of each subject are provided over a period of time. In OASIS and ADNI datasets, MRI scans are labelled as AD and Healthy controls (HC) as reported in Table 2.

As discussed earlier, three planes are generated in MRI and slice direction can be chosen from axial, sagittal, or coronal. It was observed that the coronal gives much clearer view and provides with more information. In Fig. 3**,** coronal slice is presented which gives three of the most important tissues within single slice, not found in single slice of axial or sagittal. As marked in Fig. 3, These tissues (cerebral cortex, the ventricle, and the hippocampus) are indicative of AD. While using axial or sagittal slice instead of coronal one may need to record two or more slices to cover these tissues. Therefore, coronal direction is used for analysis. Furthermore, in the coronal slices, it was observed that the central slices had more tissue portion than the ones on boarder slices. Since the tissues are indicative of AD, central slices help the system to diagnose AD accurately. The slices at the border slices have more portion of the skull and bones and prove less informative rather misleading for AD classification system. Therefore, twenty central slices are used to for the training purposes. In Fig. 4, slices of the coronal direction are presented. It can also be observed in Fig. 4, that the central slices (slice 87, 88, 89) provide much more information than earlier or later slices. Whereas, the block diagram of the proposed system used for AD diagnosis is presented in Fig. 5.

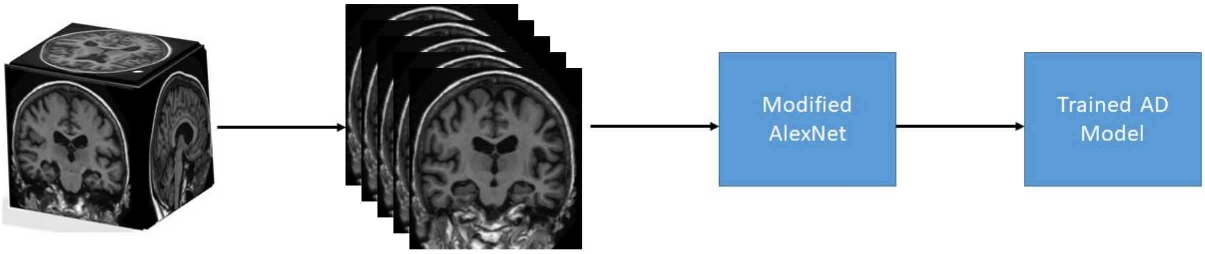



**Fig. 5: System Model**

The performance of the proposed AD classification system is discussed in detail in Section IV, Results and Discussion.

## 3.2 ADLs classification

The patients diagnosed with AD-like diseases need continuous monitoring and occasionally require assistance in performing ADLs. The condition becomes much worse in the later stages of alzheimer's and patients become more dependent on the assistance of healthcare workers. To keep track of ADLs and to minimize the human intervention as well as ensuring patient's privacy and assist overloaded hospitals and healthcare workers in reducing running costs and effectively using resources, machine-based tracking systems can play an important role. The proposed work, along with the diagnosis of alzheimer's also proposes a sensor-based framework to recognize and record daily life activities using wireless sensor networks and cloud based classification system to assist medical staff in defining appropriate requirements of the patient. The ADLs classification system not only provides machine-based recognition and record of important daily life activities but also offer appropriate assistance to the patients in performing their daily life work and achieving their daily goals. This can prolong healthy living and help in reducing the brain tissue degradation speed. It also gives more accurate feedback for the trained physicians to accurately diagnose the needs of the patient and level of assistance needed.

### *3.2.1 Development of Physical Activity Classification System*

The proposed patient monitoring architecture for the classification of ADLs and general care of the patient is presented in Fig. 6. The figure also presents sensory data communications and cloud-based classification and analysis of ADLs.

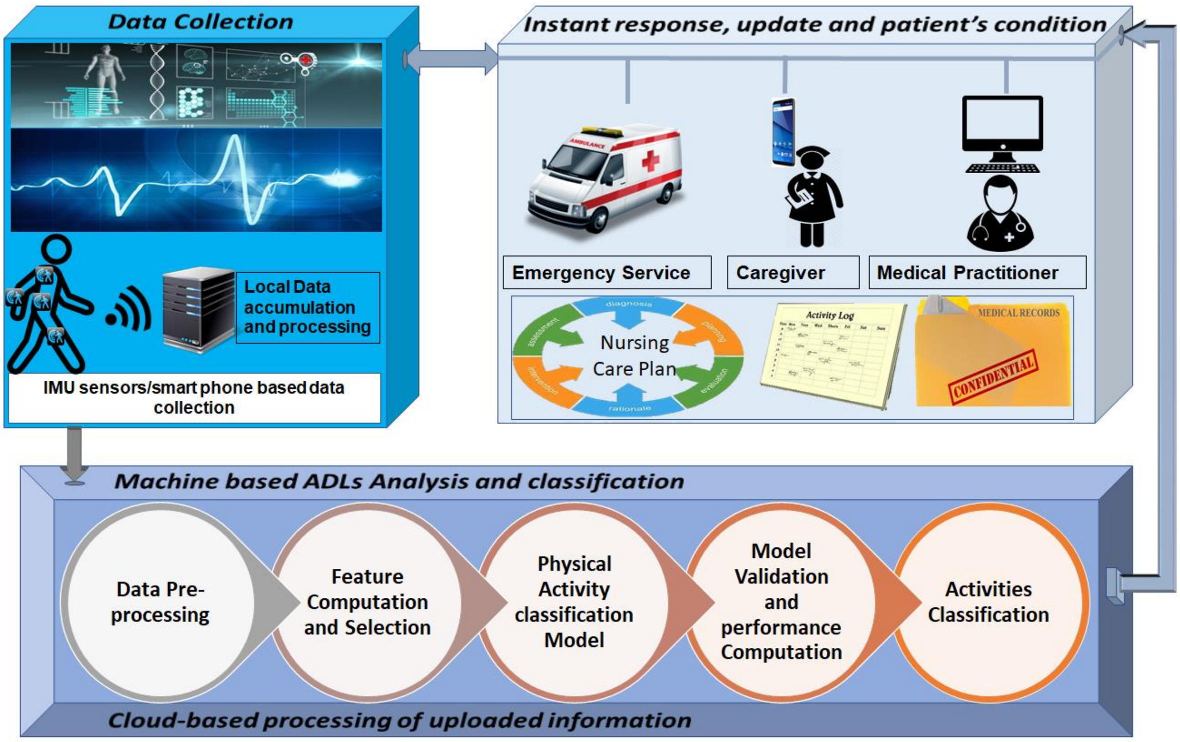



**Fig. 6: Proposed Physical Activity Classification System**

The body-worn IMU sensors records the acceleration and angular velocity data of various ADLs (sitting, standing, walking, lying etc.) and transmits wirelessly to local data accumulation unit. In case of any anomalies, the data is made instantly available to the emergency services, medical staff and care givers. Over time, the accumulated sensors' data is periodically uploaded to cloud server for onward processing and classification of ADLs. The proposed system generates medical files, activity logs and nursing care plan for long term and effective management of care services devised for the patient. Patient's sensory data and activity profile and medical records generated by cloud-based machine learning and classification system can be made available to the medical practitioners and caregiver to take further actions. The proposed system also suggests use of smart assistive technologies to communicate with emergency services in case, there arises an urgent need for assistance.

### *3.2.2 Dataset and Materials*

In this study, two datasets that use inertial sensors have been analyzed for performance evaluation of the proposed work. The details of the two datasets are as follows.

#### 3.2.2.1 Smartphone Based Single Sensor Dataset

This dataset is composed of a total of six ADLs i.e. sitting, standing, walking, lying, ascending stairs and descending stairs. These ADLs were performed by 30 subjects, ranging from 19 to 49 years of age. The subjects were wearing a smartphone at the waist level and followed a structured protocol to perform the aforementioned ADLs. The dataset contains the 3D acceleration signal data (from accelerometers) and the 3D angular velocity data (from gyroscope). The sampling frequency of the smartphone sensor was 50 Hz. The salient features of smartphone based single sensor dataset are presented in Table 3. Further details about this publicly available dataset can be found in (Anguita, Ghio, Oneto, Parra, & Reyes-Ortiz, 2013).

**Table 3: Description of the Datasets Analyzed for Physical Activity Classification**

| Author | Sampling Frequency | Sensor Location | Experiment Setting (Population) | Recorded Signals | Activities Analyzed |
|---|---|---|---|---|---|
| Anguita (Anguita et al., 2013) | 50 Hz | Waist-mounted Smartphone | Semi-naturalistic conditions (30 subjects) (19 to 48 years) | 3D Acceleraiton Signal, 3D Angular Velcovity | Standing, sitting, lying, walking, walking upstairs, walking downstairs. |
| Leutheuser (Leutheuser, et al., 2013) | 204.8 Hz | Wrist, hip, chest, ankle | Laboratory setting (23 young adults) (27 ± 7 years) | 3D Acceleraiton Signal, 3D Angular Velcovity | Walking, sitting, lying, standing, stairs up, stairs down |

#### 3.2.2.2 Multi-Sensor Based Dataset

The multi-sensor dataset was developed by utilizing four inertial sensors placed at chest, right hip, right wrist and ankle. A total of nineteen subjects (26 ± 8 years) participated in the experiment. Shimmer based wireless sensor motes were used for data collection. The sensors collected the 3D acceleration signal data and the 3D angular velocity signal data, sampled at 204.80 Hz. Further details of the dataset can be found in (Leutheuser et al., 2013). This dataset also analyzed sitting, standing, walking, lying, ascending stairs and descending stairs. Demographics of this dataset are presented in Table 3.

The ground truth information for both datasets is maintained through visual inspection of the observer at the time of data collection, which is quite essential to compute the performance of the system.

### *3.2.3 Date processing and analyzed features from Smartphone and Multi-Sensor Dataset*

A total of 76 features were analyzed from the acceleration and velocity signals ranging from statistical and frequency-based descriptors to biomechanical features. The features computation was performed using the sliding window approach on the time series data. The fixed-length of the sliding window was 2.5 sec with an overlap of 50%. Detailed information on type and number of features computed is presented in Table 4. The same feature-set was computed (Table 4) for both datasets (smartphone, multi-sensor) with only difference that the smartphone contains one sensor while multi-sensor dataset contains four sensors, resulting four times more features than smartphone.

**Table 4: Feature Computed from Accelerometer and Gyroscope Signal**

| Feature | Acceleration Signal | | | | Angular Velocity Signal | | | | No. of features |
|---|---|---|---|---|---|---|---|---|---|
| | **Ax** | **Ay** | **Az** | **$A_{MV}$** | **Gx** | **Gv** | **Gz** | **$G_{MV}$** | |
| Mean | × | × | × | × | × | × | × | × | 8 |
| Variance | × | × | × | × | × | × | × | × | 8 |
| Skewness | × | × | × | × | × | × | × | × | 8 |
| Kurtosis | × | × | × | × | × | × | × | × | 8 |
| Energy | × | × | × | × | × | × | × | × | 8 |
| Entropy | × | × | × | × | × | × | × | × | 8 |
| Spectral centroid | × | × | × | × | × | × | × | × | 8 |
| Spectral bandwidth | × | × | × | × | × | × | × | × | 8 |
| Correlation across axis | × | × | × | | × | × | × | | 6 |
| Signal magnitude area | × | × | × | | × | × | × | | 2 |
| Gravitational component | × | × | × | | | | | | 3 |
| Tilt Angle | × | | | | | | | | 1 |
| Total Features | | | | | | | | | 76 |

Ax, Ay and Az are the thee axis of acceleration signal, Gx, Gy and Gz are the three axis of Acceleration signal, $A_{MV}$ and $G_{MV}$ are the magnitude signals of the acceleration and velocity signal, respectively. The sign "×" shows the computed feature.

The expressions to compute the features listed in Table 4 (other than the simple statistical features) are described in Equations (1-7).

The magnitude vector is calculated from the three axis of acceleration signal and angular velocity as follows,

$$A_{MV} = \sqrt{{A_x}^2 + {A_y}^2 + {A_z}^2} \tag{1}$$

The time domain energy of the signal is presented as,

$$Energy = \frac{1}{N}\sum_{i=1}^{N}(|A_x(i)|^2) \tag{2}$$

here N is the total number samples across a fixed window length.

The tilt angle is calculated using the vertical gravitational component of the acceleration signal (Awais, Chiari, Ihlen, Helbostad, & Palmerini, 2018). The gravitational components are obtained by low-pass filtering the acceleration signal. The mathematical notation for tilt angle is given by

$$\mathrm{Tilt}_{\mathrm{angle}} = \mathrm{acos}(Ax) \tag{3}$$

The normalized information entropy is calculated using the FFT components of the time series signal and is presented in equation (4).

$$Entopy = -\sum_{i=1}^{N} \mathrm{p}(X_i) \times log_2(p(X_i)) \tag{4}$$

here $X_i$ is the frequency component of the time domain signal and $p(X_i)$ is the probability of the $X$ (Su, Tong, & Ji, 2014).

The spectral centroid and the bandwidth (Leutheuser et al., 2013) are computed using the Equation (5) and (6) respectively.

$$Centroid = \frac{\sum_{f=f_{min}}^{f=f_{max}} f \times E(f)}{\sum_{f=f_{min}}^{f=f_{max}} E(f)} \tag{5}$$

$$Bandwidth = \frac{\sum_{f=f_{min}}^{f=f_{max}} |centroid - f| \times E(f)}{\sum_{f=f_{min}}^{f=f_{max}} E(f)} \tag{6}$$

here $E(f)$ is the energy of the spectral component at the frequency $f$.

The Signal Magnitude Area (Lu et al., 2017), is computed as follows.

$$SMA = \frac{1}{N}\sum_{i=1}^{N}(|\mathrm{A}x(i)| + |\mathrm{A}y(i)| + |\mathrm{A}z(i)|) \tag{7}$$

It is important to note that all of the above-mentioned features (from Equation 2-7) are computed for the acceleration signal, angular velocity signal and the magnitude vector signal except the tilt angle which is computed only for the vertical gravitational component of acceleration.

Therefore, a total of 76 feature were computed from the smartphone dataset and a total of 304 features were computed from the multi sensors dataset since it contained four sensors (4x76=304).

#### *3.2.4 Feature Selection*

It is very important to analyze the computed features and to select only those features which contribute towards the classification accuracy of ADLs. Absence of feature selection approach, prior to machine learning algorithm, increases computational burden of the system which is crucial in designing the real time systems. Moreover, feature redundancy can also lead to performance degradation of the system. In this study, a correlation-based feature selection (CFS) has been implemented (Zhao et al., 2016). CFS falls under filter-based feature selection approaches and are suitable for feature subset selection without specifying a classifier during the feature selection process. On the contrary, wrapper-based methods involve a specific classifier to select the subset of features, which are only helpful for the specified classifier. Selecting feature subset independent of classifier is important in the scenarios, where the aim is to compare the performance of multiple classifiers using the same feature subset and to provide a generalized subset of features without any dependency on the classifier type.

The CFS selects the features that are highly correlated to the class and uncorrelated with each other. Thus, it evaluates the inter-correlation between the features as well as the relevance of the features in terms of predicting the classes.

#### *3.2.5 Classification and Cross Validation*

The activity classification is accomplished using the SVM classifier (polynomial kernel, complexity=1) with 10-fold cross validation procedure. The feature selection process is applied on each fold and then the performance is computed using the reduced feature-set as well as using the original set without feature selection. The classification algorithms are implemented in MATLAB using the Weka data mining software (Witten, Frank, Hall, & Pal, 2016).

### 3.3 Performance Metrices used for AD and ADLs classification

Same performance metrics were used to maintain the consistently among the results of AD and ADLs classification. The performance measures analysed this study were: accuracy, sensitivity, specificity, precision and F-measure as reported in equations (8-12).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{9}$$

$$\mathrm{Specificity} = \frac{TN}{TN + FP} \tag{10}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{11}$$

$$F - measure = \frac{2 * TP}{2 * TP + FP + FN} \times 100 \tag{12}$$

whereas TP, FP, TN, FN are representing true Positive, false positive, true negative and false negative, respectively. These terms provide number of test cases correctly and incorrectly classified.

## 4. Results and Discussion

This section presents the results of the proposed AD classification scheme. The accuracy of these results along with the comparison to the state of the art is also presented. The performance of proposed ADLs classification system is also presented. In addition, the impact of physical activity on mortality rate of diagnosed alzheimer's patients is plotted. Further details on classification accuracy of proposed works is presented as follows.

### 4.1 System Performance of AD-like diseases classification

The performance of the proposed AD-Like diseases classification system is evaluated using two publicly renowned datasets, OASIS (Marcus et al., 2010) and ADNI (Jack et al., 2008). An Nvidia GTX 1080TI based GPU was used to perform the experiments. The optimal parameters were determined by stochastic gradient descent with momentum (SGDM) algorithm with momentum value of 0.9. The mini batch size of 128, initial learning rate of value $10^{-4}$, and split ratio for training and test data is set to 0.8 in the experiment.

In each plane of OASIS dataset, the number of images for training and testing the classifier are 6656 and 1664 respectively. Similarly, for each plane in ADNI dataset, the number of images for training and testing the classifier is 34912 and 8728 respectively.

Table 5 presents different evaluation metrics of the model when all three planes generated from OASIS dataset are individually used as input. The standard deviations are also reported for each plane in Table 5. It can be seen that the coronal plane has better accuracy performance as compared to other planes because all three tissues indicative of AD are visible in the coronal plane. Table 5 also shows the performance of the AD classification system on the ADNI dataset with a notable accuracy of 98.74%.

**Table 5: Performance of AD Classification on OASIS and ADNI Database**

| Dataset | Plane | Accuracy (%) | Sensitivity (%) | Precision (%) | Specificity (%) | F-measure (%) |
|---|---|---|---|---|---|---|
| OASIS | Axial | 93.51±1.09 | 88±1.51 | 98.76±0.62 | 98.15±0.72 | 93.07±0.88 |
| OASIS | Sagittal | 94.13±1.24 | 99.70±0.22 | 97.86±1.34 | 93.61±2.02 | 98.77±0.38 |
| OASIS | Coronal | 95.93±1.12 | 92.75±2.45 | 96.94±0.82 | 92.51±1.62 | 94.70±1.23 |
| ADNI | Coronal | 98.74±0.29 | 98.50±0.45 | 98.81±0.37 | 98.21±0.87 | 98.65±0.41 |

**Table 6: Comparison with Other Methods on OASIS Dataset**

| Method | Model used | Accuracy |
|---|---|---|
| ER (ER et al., 2017) | SVM | 77.1 |
| Zhang (Zhang & Wang, 2015) | SVM | 88.27 |
| Zhang (Zhang, Dong, Phillips, Wang, 2015) | SVM | 92.36 |

| | | |
|---|---|---|
| Proposed method | CNN | 95.93 |

**Table 7: Comparison with Other Methods on ADNI Dataset**

| Method | Model used | Accuracy |
|---|---|---|
| Zhang (Zhang et al., 2016) | SVM | 83.1 |
| Gupta (Gupta et al., 2013) | Auto encoder + CNN | 93.8 |
| Payan (Payan & Montana, 2015) | 3D-CNN | 95.39 |
| Liu (Liu et al., 2014) | Auto encoder + softmax | 87.36 |
| Proposed method | CNN | 98.74 |

In comparison to other state-of-the-art techniques, the proposed scheme outperforms in both OASIS and ADNI dataset. As represented in Table 6, the proposed scheme outperforms other notable works using OASIS dataset. Using the OASIS dataset, the proposed scheme, offers an overall improvement of 18%, 7% and 5% in comparison to Varma (ER et al., 2017; J. Zhang et al., 2016), Zhang (Zhang & Wang, 2015), and Zhang (Zhang, Dong, Phillips, Wang, 2015) respectively.

Similar performance improvement was also observed while using ADNI dataset. As presented in Table 7, using the ADNI dataset, the proposed scheme offers 15%, 11%, 5% and 3% improvement in comparison to Zhang (Zhang et al., 2016), Liu (Liu et al., 2014), Gupta (Gupta et al., 2013), and Payan (Payan & Montana, 2015) respectively.

The improved accuracy offered by the proposed scheme, as evidenced in evaluation using both ADNI and OASIS datasets, offers added authenticity compared to other AD-like diseases diagnosis schemes. In addition to the accurate diagnosis of AD, physical activities are another important aspect in keeping the diagnosed patients healthier for longer time and prolonging their life (Beckett, Ardern, & Rotondi, 2015; Debove, Bru, Couderc, Noé, & Paillard, 2017; Scarmeas et al., 2011). Therefore, an ADLs classification system is proposed to automate the monitoring of ADLs of the diagnosed patients. This work offers a novel contribution to knowledgebase and facilitates automated activity analysis and logging. Additional details on results and performance analysis of ADLs classification system are presented in Section 4.2.

## 4.2 System Performance of ADLs classification

One of the aims of this study is to transform the inertial sensor based physical activity systems from healthy population to a challenging AD based population to objectively quantify the ADLs accurately. To facilitate the medical staff, an activity profile of each subject is created, which can help in activity planning, future recommendations and prediction of progression in alzheimer's patients. Performance evaluation of ADLs classification system is performed using two separate datasets, further details of which can be found in upcoming passages.

### *4.2.1 Performance Analysis of Smartphone Based Physical Activity Classification System*

In smartphone based physical activity classification system, the performance is computed for the original feature set (without feature selection) and with the subset selected by the feature selection approach. Use of original feature set revealed very encouraging results with an overall accuracy of 98.1%. This shows that the proposed method can accurately classify the ADLs with very high accuracy. The accuracy obtained using the reduced feature set was 97.0%, which is slightly lower (1.1%) than the original feature set. A significant reduction in the feature set was observed when using CFS, where CFS selected 25 features (average selected features across all folds) out of 76 features. Use of CFS resulted in 67% reduction in features overhead at the cost of 1.1% of system accuracy. Depending on requirements, a trade-off can be established between feature set reduction and overall accuracy. However, use of CFS becomes a necessity when real time system is implemented as the reduction in feature set notably reduces computational burden. The confusion matrix of the system for reduced feature set is presented in Table 8. The average and standard deviation of all performance metrics obtained from smartphones-based activity recognition are reported in Table 9. It is quite evident from these measures that proposed system was able to accurately classify between various ADLs with very high performance (above 95%).

**Table 8. Confusion Matrix of Smartphone based System with Reduced Feature set**

| Classified as → | Stand | Sit | Lie | Walk | Stairs Down | Stairs Up |
|---|---|---|---|---|---|---|
| **Stand** | 1837 | 69 | 0 | 0 | 0 | 0 |
| **Sit** | 87 | 1690 | 0 | 0 | 0 | 0 |
| **Lie** | 0 | 0 | 1944 | 0 | 0 | 0 |
| **Walk** | 0 | 0 | 0 | 1681 | 16 | 25 |
| **Stairs Down** | 0 | 0 | 0 | 12 | 1356 | 38 |
| **Stairs Up** | 0 | 0 | 0 | 39 | 20 | 1485 |

**Table 9. Overall Performance of Physical Activity Classification System on Smartphone and Multi-sensor Dataset**

| Dataset | Accuracy (%) | Sensitivity (%) | Precision (%) | Specificity (%) | F-measure (%) |
|---|---|---|---|---|---|
| **Smartphone** | 99±0.57 | 96.95±1.69 | 97±1.64 | 96.41±0.36 | 96.97±1.62 |
| **Multi-sensor** | 99.60±0.32 | 98.41±1.32 | 98.29±1.70 | 99.71±0.33 | 98.32±1.48 |

### *4.2.2 Performance Analysis of the Multi-Sensor Based Physical Activity Classification System*

The performance analysis of multi-sensor based physical activity classification system resulted in very high system performance as well, where 98.2% accuracy was achieved using original feature set. Similarly, the system performed substantially well on the reduced feature set with F-measure of 98.3%. The feature selection has not only reduced the number of features by 81% (from 304 to 55) but it also improved the performance as well. The improvement is primarily attributed to the removal of features which negatively contributed to the accuracy and thus removing them resulted in improved outcome. The confusion matrix obtained using the reduced feature set is presented in Table 10.

**Table 10. Confusion Matrix of the Multi-sensor based System with Reduced Feature set**

| Classified as → | Stand | Sit | Lie | Walk | Stairs Down | Stairs Up |
|---|---|---|---|---|---|---|
| **Stand** | 896 | 1 | 0 | 5 | 0 | 2 |
| **Sit** | 1 | 896 | 8 | 0 | 0 | 0 |
| **Lie** | 1 | 1 | 910 | 0 | 0 | 0 |
| **Walk** | 3 | 0 | 0 | 4050 | 18 | 18 |
| **Stairs Down** | 0 | 0 | 0 | 13 | 509 | 3 |
| **Stairs Up** | 0 | 0 | 0 | 18 | 4 | 616 |

The proposed system is recognizing ADLs with very high accuracy, where each performance measure is above 95%. Class-wise F-measure of each classified ADL is presented in Fig. 7. The rationale for using F-measure is to represent performance of each class in an unbiased way (see Fig. 7), since accuracy can be influenced by large number of true negatives and provides biased measure for uneven/imbalanced datasets (where certain classes are underrepresented as compared to others). Thus, a more balanced and reliable metric in the form of F-measure is computed for each class to provide a balance between precision and recall as well as to provide unbiased performance measure for imbalanced classes. The proposed physical activity classification system performed significant well on both datasets: smartphone based dataset and multi sensors based dataset. The performance of all six classes is above 95% for both datasets. These results are quite significant and encouraging to use the proposed system to monitor the ADLs of AD patients. For instance, a single sensor-based system is feasible when the intentions are to utilize the system in outdoor environment, where wear-ability and battery life are major concerns and slight degradation in performance is acceptable. On the other hand, multi sensor-based system are highly effective when the patients are being monitored in clinical environments, and high performance is desired for each of the ADLs.

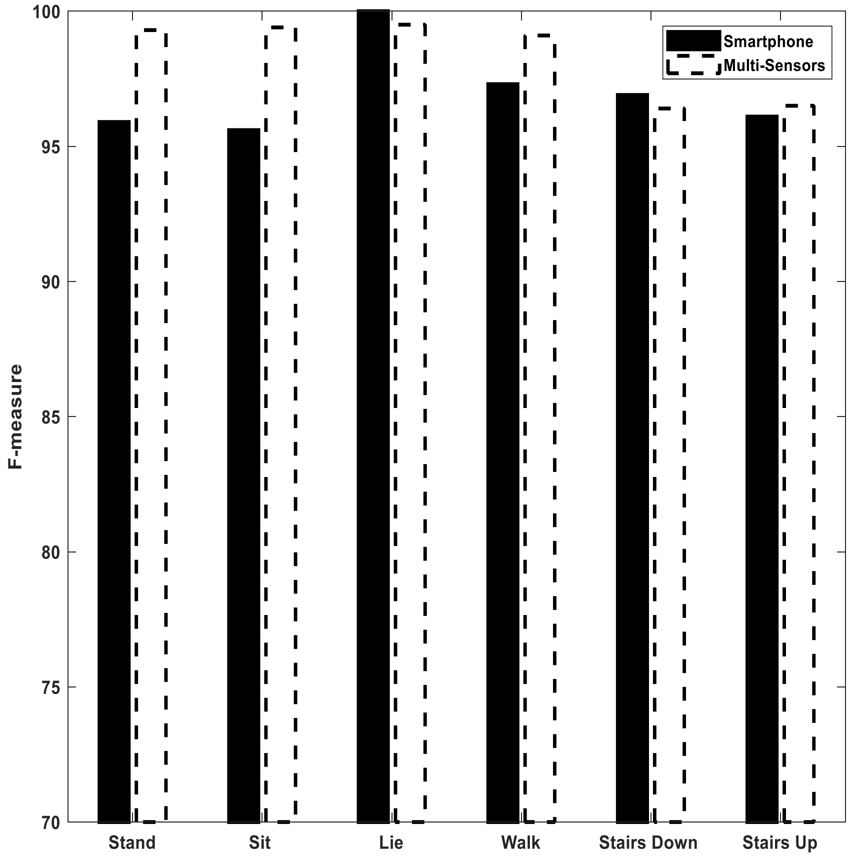



**Fig. 7: Performance Analysis of Smartphone vs Multi-sensors based Activity Classification System for each Single Analyzed ADL**

The comparison between the performances of the proposed system with the existing methods (including the models used) is presented in Table 11. The standard deviation of the proposed system in also presented. It is quite evident from the results that the proposed method outperforms the existing systems in using both smartphone-based and multi sensors based dataset. A performance improvement of up to 6.3% is witnessed in smartphone based dataset whereas 8.7% improvement is witnessed in multi sensors dataset, when compared to the existing methods. These findings encourage use the wearable sensor based activity classification for AD patients to monitor their routine ADLs.

**Table 11. Performance Comparison of Smartphone and Multi-sensor Dataset with Other Methods**

| **Smartphone Dataset** | | | **Multi-Sensors dataset** | | |
|---|---|---|---|---|---|
| Author | Model used | Accuracy (%) | Author | Model used | Accuracy (%) |
| Ronao (Ronao & Cho, 2014) | Hidden Markov Model | 91.8 | (Leutheuser et al., 2013) | Hierarchical Classification | 89.6 |
| Anguita (Anguita et al., 2013) | SVM | 96.0 | (Zdravevski et al., 2017) | SVM, Random Forest | 93.4 |
| Proposed method | SVM | 98.1± 1.4 | Proposed method | SVM | 98.3± 1.9 |

The results show that the inertial sensors based physical activity classification system can accurately monitor the activity performed. The strength of the proposed system is wear-ability and portability which is a key factor for long term monitoring of patients with AD-like diseases. Proposed work can provide feedback to the healthcare practitioners and caregivers about the nature and proportions of activities performed not only for shorter duration but also for longer duration i.e. weeks and months. The activity profile can provide a better idea of patient's functional independence, mobility patterns and responses to certain interventions that can be in the forms of medications, exercises, therapies. In this way, the proposed system can assist medical staff in ensuring prolonged healthy living for the patients diagnosed with AD-like diseases. It also reduces the management effort of the medical staff and healthcare workers.

Patients diagnosed with alzheimer's disease are encouraged to maintain healthy living, so much so that their survivability is reported to depend on level of physical activity. In Fig. 8, the patients diagnosed with alzheimer's are categorized with respect to physical activity with no, moderate and high physical activity level (NPA, MPA, HPA). As presented in the figure, alzheimer's patients with NPA have a relatively very low survival rate (i.e. 0.09 %), compared to the patients with HPA (Beckett, Ardern, & Rotondi, 2015; Debove, Bru, Couderc, Noé, & Paillard, 2017; Scarmeas et al., 2011). Alzheimer's patients with HPA are expected to have over 4 times higher survival rate compared to patients with NPA. Due the high correlation between alzheimer's and physical activity, which is evident from the works of (Beckett, Ardern, & Rotondi, 2015; Debove, Bru, Couderc, Noé, & Paillard, 2017; Scarmeas et al., 2011), the proposed work offers a framework to not only assist in diagnosis of alzheimer's but also to support medical staff with automated recording of physical activities.

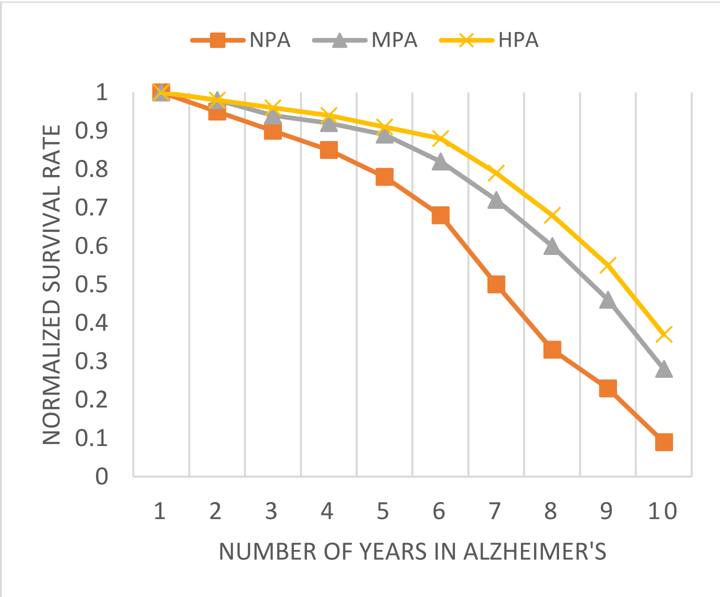



**Fig. 8: Survival Rate of Alzheimer's patients Depending on Level of Physical Activity**

The normal perception is that performing vigorous and intensive activity (running, jumping, cycling) improves the functional independence and strength. However, such activities are not suitable for the population suffering from neurodegenerative disease such as AD. This is because such population is unable to perform intense physical activities and their mobility patterns becomes limited. In these conditions, one can monitor the less intensive activities (sitting, standing, walking, lying, ascending stairs, descending stairs etc.), as these can play a significant role in letting the individuals as well as medical experts aware of the physical activities carried out on daily basis. It also maintains a certain level of functional independence while performing daily life activities. Hence, the proposed system can play a vital role in determining and improving the quality of life in population with AD-like diseases.

## 5. Conclusion

Accurate diagnosis of alzheimer's and post diagnosis healthy living are key to defeating alzheimer's. Referring to high volume of AD patients and huge economic impact of nearly US $1 trillion, the importance of investigation can easily be established. To improve the diagnosis accuracy and to assist over stressed medical experts, this paper proposed a machine-based analysis of the AD-like diseases which offered improved diagnosis accuracy in comparison to state of the art. To further assist the alzheimer's patients and caretakers, a post-diagnosis monitoring system was proposed to log the daily life activities of the patients, thus, enabling future systems to develop suggestions and activities plan for the patients to extend the healthy living and minimize human assistance for AD patients. In the proposed system, for both diagnosis and post-diagnosis ADL monitoring systems, relatively higher accuracy is achieved. Furthermore, this paper correlates the importance of high accuracy AD diagnosis with physical activities and how these activities can be logged without human intervention with high accuracy. The work presented in this paper serves as a base for quantitative analysis of AD-like diseases and how well it can be controlled with certain volume of physical activities.

In the future, this work can further be extended to give quantitative correlation between AD-like diseases and their progression as a function of physical activities and how much the progression of AD-like diseases can be delayed by incorporating certain amount of activities in life of alzheimer's patients.

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